Automatic Calibration of Modified FM Synthesis to Harmonic Sounds using Genetic Algorithms

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ABSTRACT

Many audio synthesis techniques have been successful in reproducing the sounds of musical instruments. Several of these techniques require parameters calibration. However, this task can be difficult and time-consuming especially when there is not intuitive correspondence between a parameter value and the change in the produced sound. Searching the parameter space for a given synthesis technique is, therefore, a task more naturally suited to an automatic optimization scheme.

Genetic algorithms (GA) have been used rather extensively for this purpose, and in particular for calibrating Classic FM (ClassicFM) synthesis to mimic recorded harmonic sounds. In this work, we use GA to further explore its modified counterpart, Modified FM (ModFM), which has not been used as widely, and its ability to produce musical sounds not as fully explored. We completely automize the calibration of a ModFM synthesis model for the reconstruction of harmonic instrument tones using GA. In this algorithm, we refine parameters and operators such as crossover probability or mutation operator for closer match. As an evaluation, we show that GA system automatically generates harmonic musical instrument sounds closely matching the target recordings, a match comparable to the application of GA to ClassicFM synthesis.

1. INTRODUCTION

Replicating the sounds of musical instruments using parametric synthesis techniques is a problem frequently addressed in the field of computer music. The success of any particular synthesis algorithm, is dependent, in part, on the selection of suitable controls and synthesis parameters. Manually estimating parameters for a particular synthesis algorithm can be difficult and time consuming, especially if there is no intuitive relationship between the parameter values and the produced sound. Thus, diverse optimization methods have been used for automatic calibration, such as Particle Swarm [1], HMM [2], Neural Nets [3], Cellular Automata [4], Genetic Algorithms [5], etc.

It has been suggested that Genetic Algorithms (GA) are well suited to matching musical instrument tones (as mea-

sured by the error in feature vector space) [3]. Indeed, GA have been used extensively for estimating the parameters of synthesis techniques such as additive synthesis [6], subtractive synthesis [3], granular synthesis [7] or frequency modulation (FM) synthesis [8].

The use of GA for ClassicFM parameter estimation, has not yet been extended to its modified counterpart, Modified FM (ModFM), a modulation technique derived from ClassicFM. ModFM is built on Hutchins' 1975 work [9] on exponential FM with analog signals. In 1977, Moorer [10] introduced the ModFM formula presented as one of the more practical of various well-known closed-form formulas. It is not before 2010 with Lazzarini [11] that this technique was reintroduced. While ModFM is not considered to be a substitute for ClassicFM, it can offer an alternative when ClassicFM does not provide the desired effect. In this work, we further explore this less-known synthesis technique, and present a method, using GA, to match harmonic tones produced by musical instruments. An evaluation of simulated and recorded target sounds is presented in Section 5. As our system is also applicable to ClassicFM, we also include a comparison of the system's performances in both synthesis techniques. Sound examples are available for public audition [12].

2. CLASSIC FM SYNTHESIS AND AUTOMATIC CALIBRATION

FM synthesis, pioneered by Chowning, is a technique whereby the frequency of an carrier oscillator is altered, or "distorted", in accordance with the amplitude of a modulating signal [13]. As shown in Chowning's original paper, and in much of the literature that followed, FM synthesis made it possible to create complex spectra with only a limited number of oscillators. Chowning's work included several hand-tailored parameter settings for various instruments as well as parameters appropriate to design woodwind, brass, vocal, and percussive instruments based on simulating the properties of those instruments. The estimation of FM parameters for which "recipes" did not exist however, was more difficult for users of the technique.

Morrill's study of FM trumpet tones [14] followed Chowning's work in trying to determine parameters based on detailed knowledge of the trumpet. Morrill presented single and double carrier architectures for the trumpet and clearly identified the limitations of single carrier architecture. He also pointed out the difficulty in predicting the spectral output of the double carrier architecture. Since then, more

complex ClassicFM architectures involving several carriers and modulators have been developed, such as nested modulator FM, double FM or feedback FM synthesis [5]. Though these algorithms have made it possible to synthesize more complex sounds, the increased complexity have made the search of parameters even more difficult.

Justice [15] was one of the first to propose a method to determine these parameters. He introduced a Hilbert transform procedure to decompose a signal into parameters for a single carrier FM architecture. The procedure attempted to produce a matched FM signal close to the original, leaving the user to tweak the parameters as desired. However, Justice matched FM-generated signals and not those of acoustic musical instruments.

Later, Beauchamp [16] developed a frequency-domain method to find FM parameters as part of a larger study on brightness matching. He used a single carrier-modulator pair with a centroid-controlled modulation index to match the time-varying spectral centroid of the original signal. Though the level of control was too coarse to provide a good perceptual match, the technique was notable in its attempt to perform an automated spectral match. Along the same lines, Delprat et al. used a wavelet analysis and a Gabor transform to find spectral trajectories to estimate the modulation indexes [17]. However, their technique didn't automate the process of searching for the complete set of synthesis parameters; it only focussed on modulation indexes.

Horner et al. were one of the first to attempt to do parameter optimization for more complex FM synthesis architecture [8]. They used GA to optimize the modulation indices and carrier and modulator frequencies for various numbers of carriers. The relative spectral error between the original and matched spectra served as the fitness function guiding the GA's search to the best FM parameters. Most matched instruments required three to five carriers for a good match. Horner [18] also applied GA to the other known FM synthesis architectures such as nested modulator FM matching and feedback FM synthesis.

With the increasing popularity of sampling (largely due to its ability to produce more realistic acoustic sound and the decreasing cost of storage), research and applications of FM declined gradually only to be rekindled more recently: Lazzaro showed how a single mathematical function can model a subtractive synthesis technique [19] and therefore be considered as a modulation technique alongside FM synthesis. He also introduced some novel methods of formant analysis and synthesis [20] using ModFM [11], a modified version of ClassicFM.

3. MODIFIED FM SYNTHESIS

The general equation for a one-carrier one-modulator FM synthesis is given by

$$
\begin{aligned}
x_{FM}(t) &= \cos\left(\omega_c + I\sin(\omega_m t + \phi_m) + \phi_c\right) \\
&= \sum_{n=-\infty}^{\infty} J_n(z)\cos[\omega_c t + n(\omega_m t + \phi_m) + \phi_c]
\end{aligned}
\tag{1}
$$

where I is the index of modulation, ω_c and ω_m are the carrier and modulator angular frequencies, ϕ_c and ϕ_m are the carrier and modulator phases, and J_n is the Bessel function of the first kind of order n, given by

$$
J_n(z) = \sum_{m=0}^{\infty} (-1)^m \frac{(I/2)^{n+2m}}{m!(m+n)!}
\tag{2}
$$

The ModFM technique can be derived from ClassicFM by making small modifications to (1). By appropriately setting the carrier and modulator phases, we obtain

$$
\cos[\omega_c + I\cos(\omega_m t)]] = \Re\{e^{j\omega_c t + jI\cos(\omega_m t)}\}
\tag{3}
$$

and changing the modulation index so that it is purely imaginary (by multiplying I by j) yields

$$
x(t) = e^{I\cos(\omega_m t)}\cos(\omega_c t),
\tag{4}
$$

a variant of FM synthesis employing a purely imaginary index of modulation and producing a different set of scaling functions for the FM spectrum:

$$
\begin{aligned}
x(t) &= B_0(I)cos(\omega_c t) + \\
&\quad \sum_{n=1}^{\infty} B_n(I)(\cos(\omega_c t - n\omega_m t) + \\
&\quad \cos(\omega_c t + n\omega_m t)),
\end{aligned}
\tag{5}
$$

where B_n is the modified Bessel function of order n,

$$
B_n(I) = \sum_{m=0}^{\infty} \frac{(I/2)^{n+2m}}{m!(m+n)!},
\tag{6}
$$

which, unlike J_n, is a unipolar signal: $B_{n+1}(k) < B_n(k)$. If FM synthesis is seen as a combination of sinusoids ring-modulated by real sinusoidal waveshaper signals, ModFM is then based on a sinusoid ring-modulated by a complex exponential waveshaper signal.
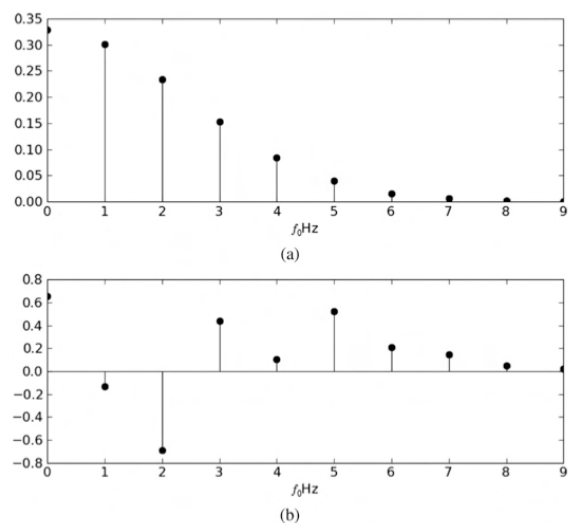

Figure 1. Comparison between ModFM (a) and ClassicFM (b) spectra for $I = 5$ and $\frac{\omega_c}{\omega_m} = 1$

Figure 1 shows a comparison between ModFM and ClassicFM spectra, produced with the same parameters. It can be seen that the major differences are in ModFM's monotonically decreasing spectrum. Moreover, the absence of phase-reversed partials may allow for a more predictable result when combining several ModFM carriers.

3.1 ModFM synthesis properties

ModFM synthesis instrument design takes advantage of the various concepts and ideas associated with ClassicFM synthesis. In particular we observe the following principles:

1. The carrier-to-modulator frequency ratio $\frac{f_c}{f_m}$ will determine the harmonicity of the spectrum and its fundamental frequency, if any.

2. If $\frac{f_c}{f_m}$ can be represented as $\frac{N_1}{N_2}$, where $\frac{N_1}{N_2}$ are small integers with no common factor, the spectrum is harmonic and we have $f_0 = \frac{f_c}{N_1} = \frac{f_m}{N_2}$. When $\frac{N_1}{N_2}$ is neither rational nor small, the spectrum will be inharmonic.

3. If $N_2 = 1$, the spectrum will contain all harmonics; when $N_2 > 1$, every $N_2{}^{th}$ harmonic is missing.

4. For integers N_1 and N_2, the carrier frequency f_c will always be the $N_1{}^{th}$ harmonic in the spectrum.

Lazzarini et al., claim that the ClassicFM recipes may be used successfully when applied to ModFM and in some cases, resulted in improved synthesis [11]. It is not our aim here to compare the two techniques, or make any claims of one being more suitable than the other. Rather, we would like to further explore ModFM by applying a GA to better estimate synthesis parameters, and further explore its ability to produce musical instrument sounds.

4. PARAMETER ESTIMATION USING GENETIC ALGORITHMS

Genetic Algorithms (GA) were first introduced by Holland [21] and have since been applied to a wide variety of problems from electric circuit design [22] to music improvisation [23]. In a GA, a population of strings called *chromosomes*, which encode candidate solutions (individuals) to an optimization problem, evolves toward better solutions. The evolution usually starts with a first generation of randomly generated individuals. At each generation, the fitness of every individual in the population is evaluated. Multiple individuals are then stochastically selected based on their fitness from the current population, and modified with genetic operators to form a new population. Genetic operators could be cross-over, reproduction or mutation operators. The new population is finally used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached. If the algorithm has terminated due to a maximum number of generations, a satisfactory solution may or may not have been reached. Figure 2 illustrates the principle of this family of algorithms.
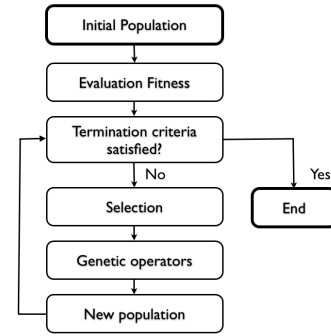

Figure 2. GA algorithm principles

4.1 System design

Given an harmonic target sound, our system has been designed to converge to the most similar ModFM synthesized sound. The process is completely automatic and only requires two inputs: an harmonic target sound and the number of carriers to use in the ModFM synthesis architecture (see Figure 3). As ModFM and ClassicFM share the same theoretical foundation, the design of our system has been inspired by Horner's work [8] (who successfully applied GA to ClassicFM) with slight differences being:

- use of an automatic fundamental frequency detection algorithm by the fitness function,

- an amplitude envelope estimation and smoothing for the carrier,

- a limit to the number of harmonics used by the optimization (harmonics must have sufficiently significant amplitude compared to the fundamental),

- a refined GA which used more efficient and adapted mutation operator and refined genetic parameters,
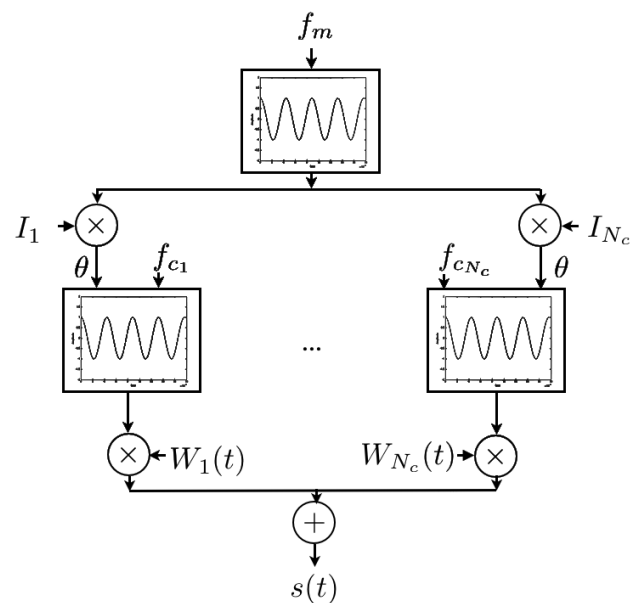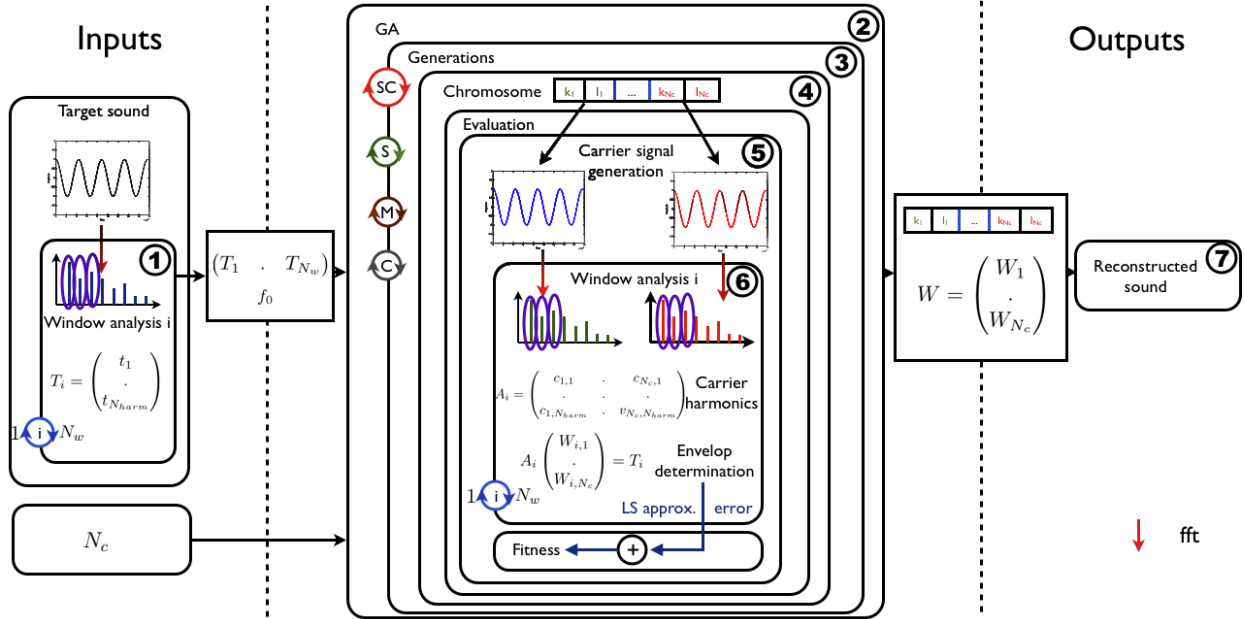

Figure 3. ModFM architecture

Figure 4. System overview. N_{harm}: number of harmonics taking into account; N_w: number of analysis windows; N_c: number of carriers; f_0: target fundamental frequency; SC: Stopping Criteria; S: Selection operator; M: Mutation operator; C: Crossover operator

- and most notably, the use of the ModFM synthesis model in lieu of ClassicFM.

4.2 ModFM synthesis model

As in previous research [8, 11, 13, 14], we use a synthesis model consisting of a single modulator and multiple parallel carriers, as shown in Figure 3. Each carrier has the same modulation frequency f_m but a different carrier frequency f_{c_i} and modulation index I_i. An envelop $W_i(t)$, which can take negative values, is applied to each carrier.

In our ModFM model, the modulation indices are not time-varying. Though time-varying modulation indices cause a time-varying presence of harmonics, a spectral characteristic of sounds produced by acoustic instruments, we focus on the steady-state for matching purposes.

As we are only dealing with harmonic target sounds, there is a constraint placed on the carrier frequencies to be integer multiples of the modulation frequency. This constraint makes it possible to take advantage of the properties of ModFM synthesis listed in Section 3.1.

To ensure spectral matching between synthesis and target sounds, the modulating frequency f_m is set to the target fundamental frequency f_0. The parameters which are optimized for this ModFM model are, therefore, the modulation indices, carrier frequencies and carriers envelops of each of the carriers.

4.3 Pre-analysis

The first step in our system is a pre-analysis of the target sound (see Step 1 in Figure 4). A Fourier transform is performed on the ith window analysis and the magnitudes of the N_{harm} first harmonics are extracted and stored in a vector T_i. This process is iterated on the whole duration of

the sound to get the matrix $\boldsymbol{T}$ containing the magnitudes of the N_{harm} first harmonics on each window analysis. This matrix is used as the optimization objective. An other Fourier transform is performed on the steady-state segment of the sound to extract the fundamental frequency. Table 1 gives the parameters used to perform each short spectral analysis in our system.

4.4 Applying GA

The next step is the parameter optimization using a GA (see Step 2 in Figure 4).

4.4.1 Population and chromosomes

Step 3 in in Figure 4 shows the populations which are evolved during each generation. The parameters to optimize in our system are the couples: (carrier frequency, modulation index) for each carrier (see Figure 3). These parameters are represented by a chromosome, shown in Step 4 in Figure 4. Integers $k_1,..,k_{N_c}$ are multipliers for the carrier frequencies ($f_c(i) = k_i * f_m$), and $I_1, .., I_{N_c}$ are the fixed modulation indexes and are real-valued parameters. To limit the complexity of the search, we constrain the multipliers for the carrier frequencies to the interval $[0, 10]$ and the modulation indices to the interval $[0, 20]$. These restrictions are compatible with both Lazzarini's recommendations [11] about parameters calibration in ModFM and ClassicFM.

4.4.2 Evaluation: fitness score

Each chromosome is evaluated. The first step is generating the carrier signals using the couples: (carrier frequency, modulation) in the modFM architecture (see Step 5 in Figure 4). A Fourier transform is performed on the ith window analysis and the magnitudes of the N_{harm} first harmonics

are extracted for each carrier and stored in the matrix A_i. $A_{i_{k,l}}$ is the magnitude of lth harmonic of the kth carrier on the ith analysis window. The equation

$$A_i \begin{pmatrix} W_{i,1} \\ \vdots \\ W_{i,N_c} \end{pmatrix} = T_i$$

is then solved with the least squared regression method, a classic method for finding an approximate solution to an overdetermined equation system (see Step 6). Vector W_i represents the coefficients to be applied to each carrier for the window i to obtain the closest fit to the target harmonic magnitudes. As we are using 50 % overlapping analysis windows, for each half time window, we get two coefficients. To reconstruct the carriers envelopes, the mean of these coefficients is taken. This process is iterated on the whole duration of the sound and at the end, produces W, the matrix whose rows represent the envelopes to apply to the carrier signals. Finally, the fitness score for the chromosome is the accumulated approximation error in the least square regression method. This evaluation is performed on the whole population of chromosomes (see Step 3 in Figure 4).

4.4.3 Selection strategy

Once every chromosome has been evaluated, if none of the stopping criteria has been reached (see Section 4.4.5), a new generation is generated. The N_{elite} best chromosomes are kept and the rest of the population is generated with crossover or mutation on selected chromosomes (see section 4.4.4). These chromosomes are selected using the binary tournament selection. In this type of selection, two chromosomes are selected randomly in the population, their fitnesses are compared and the best is selected.

4.4.4 Genetic operators

A single crossover point on both of the two selected chromosomes is selected. All parameters beyond that point in the chromosome are swapped between the two selected chromosomes. The resulting chromosomes are used in the new generation. The proportion of chromosomes generated by crossover is given in Table 2.

Gaussian mutation is used in this system. A random number from a gaussian distribution is added to each parameter of the chromosome. This gaussian distribution is centered on the middle of the parameter definition interval and its standard deviation decreases when the number of generations is increasing. This dynamic standard deviation makes it possible to have a broad exploration of the parameter

Analysis window size	10 ms
Overlapping	5 ms
Zero padding factor	4
Spectral resolution	20 Hz
Number of harmonics N_{harm}	10

Table 1. Parameters for the short spectral analysis

Population	100
Max Generation N_{gen}	300
Stopping criteria SC	weighted change in the fitness $< 10^{-10}$ over 50 generations
Selection operator S	binary tournament selection
Elite children N_{elite}	2
Mutation operator M	gaussian
Crossover operator C	1-point crossover
Crossover proportion	80%

Table 2. Parameters for the GA

space at the beginning of the evolution and to fine tune the parameters at the end of the evolution.

The initial standard deviation is given by $v(2) - v(1)$ with $v(2)$ the upper bound of the parameter definition interval and $v(1)$ the lower bound of the parameter definition interval. The standard deviation at the kth generation is given by

$$\sigma_k = \sigma_{k-1}(1 - \frac{k}{N_{gen}}), \tag{7}$$

where σ_k is the standard deviation at generation k and N_{gen} is the maximum number of generations (see Table 2).

4.4.5 Stopping criteria

The optimization process terminates if the system reaches the 300th generation or the weighted change in the fitness, given by

$$\delta_n = \sum_{i=1}^{N} (\frac{1}{2})^{N-i}(f_{n+1-i} - f_{n-k}), \tag{8}$$

is less than 10^{-10} over 50 generations. Equation 8 is the weighted change at generation n, f_k is the best fitness score at generation k, N = 50 if $n \geq 50$ otherwise $N = n$.

4.4.6 Sound reconstruction

The output of the GA is the best chromosome and a set of envelopes for each carriers (see Step 7). The carrier signals are generated using the parameters contained in the best chromosome. The envelopes are *smoothed* using a low pass filter (cut-off frequency : 22 Hz) before being applied to the carriers to avoid *clicking* phenomena. Finally the enveloped carriers are added to get the synthesized sound (see Figure 3). We use a sampling frequency equals to 44100 Hz and 16 bits encoding.

5. SYSTEM EVALUATION AND RESULTS

5.1 Experiment: Simulated sounds

A preliminary experiment was intended to test the convergence of our system. Sounds produced using ModFM were used as target sounds, so we would know there would be a match that could be found by "reverse engineering".

Three experiments were conducted: E1, E2 and E3, using 2, 4 and 6 carrier architecture, respectively. The parameters (envelops and synthesis parameters) were generated
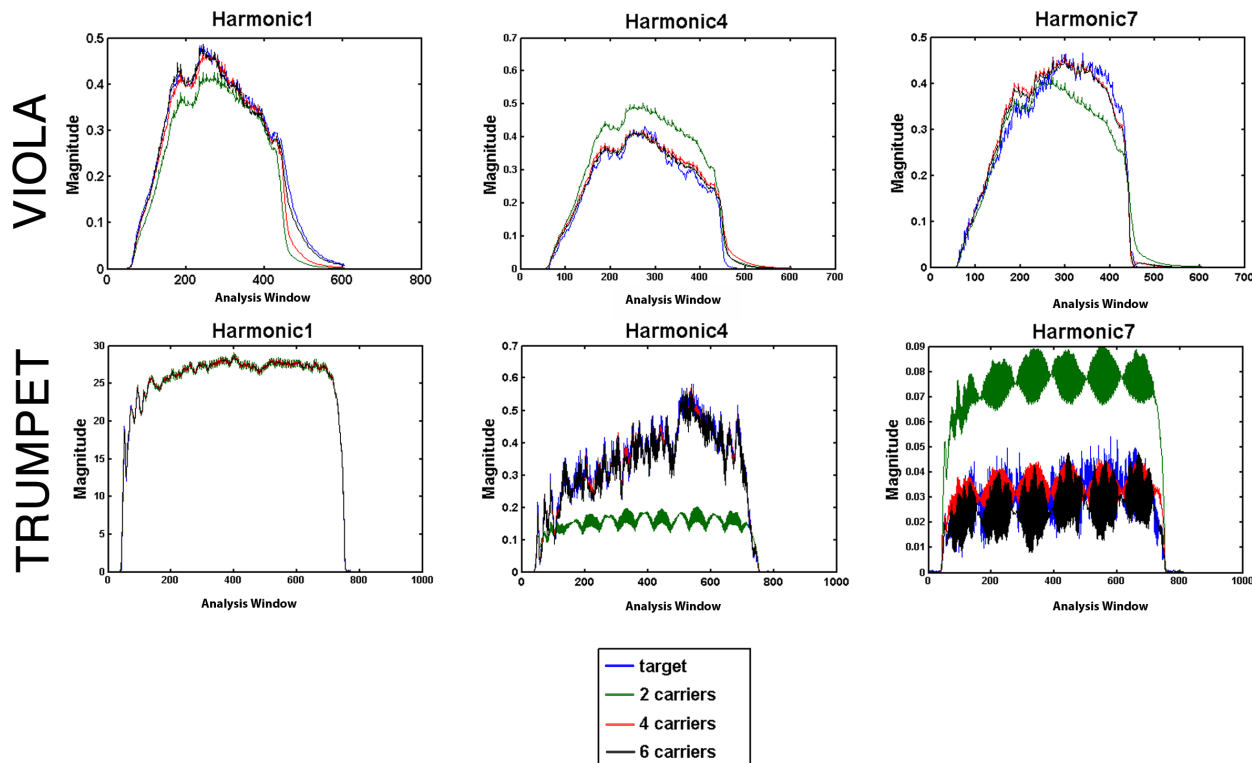
Figure 5. Harmonics for trumpet and viola sounds (ModFM)

randomly. For each experiment, the system was run 4 times with, each time, different parameters for the target sounds. The results can be consulted on our website [12].

Our system converges very quickly toward the target sound. One interesting result, however, is that in some cases our system finds a set of parameters different from those used to produce the target, but nevertheless leading to a sound that is a very close match. Indeed, as different carriers are combined and envelopes are applied, there could be redundancy in the space of synthesizable sounds. This could prove useful since a user could change the parameter values around those optimized and explore the *surroundings* of the sound. If, for a given target sound, we can get several sets of optimized parameters, it would give us several *surroundings* to explore and we can expect that they would sound different.

5.2 Experiment: Recorded sounds

For our second experiment, we use instrument sounds recorded in an anechoic chamber from the MIS database [24]. Each sound is approximately 2 seconds long. The sound set includes the 13 following instruments: alto sax, bass, bassoon, clarinet, cello, flute, horn, oboe, trombone, trumpet, tuba, viola and violin. For each sound, the 3 experiments, E1, E2 and E3 were performed. The results can be consulted on our website [12].

5.3 Comparison between ClassicFM and ModFM

We ran the same experiments using ClassicFM to compare the performances of our system to optimize ClassicFM and ModFM. Nothing in our system is specific to ModFM.

The fitness function, the analysis parameters and the genetic operators are generic and can also be applied to ClassicFM. The specifications for the ClassicFM implementation are the same that the ones presented in Section 4.1 except the ModFM carriers/modulators that are now replaced by those of ClassicFM. We followed the same experimental protocol that is described in Section 5.2. A comparison between the results of the two experiments and is available on our website [12].

6. DISCUSSION

Table 3 gives the distribution of the fitness and of the number of generations required to converge. The GA is converging about 13 % faster on average using ModFM than ClassicFM for a loss of 1% on average in fitness. It would be natural to think that the more carriers we optimize, the longer the system takes to converge but when we look at the results, it is not always the case (oboe, tuba, clarinet, etc). Results for the flute and the sax appear to be outliers for both synthesis methods as the GA doesn't converge or converge toward a high fitness value. This may be a result of the limited synthesis architecture being used. The fitness

Param.	ClassicFM		ModFM	
	μ	SD	μ	SD
Fitness	51.94	77.96	52.60	87.52
Gen. to conv.	99.24	69.24	87.60	42.57

Table 3. Number of generations needed to converge and fitness distribution
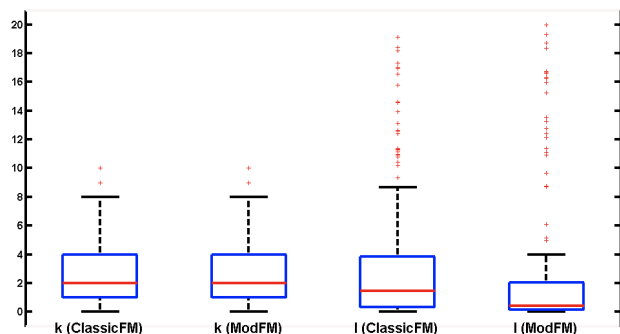
Figure 6. Synthesis parameter distribution

Figure 7. Target and best candidate spectra for viola and trumpet with 4 carriers (ModFM)

score, which is the approximate error for the harmonics, is neither an absolute nor perceptual measure and varies between the different target sounds (see SD in Table 3). For example, the best synthesized sound for a Viola sounds as good as the one for the trombone, but their respective fitness scores are very different (Viola best fitness: 24.22 and Trombone best fitness: 117.60).

Overall, sounds generated with ModFM sound less bright than those generated with ClassicFM. Nevertheless, the best fitness score is higher for ModFM, 30 times over 45 experiments. When their spectrograms are compared for the same target sound, we observe more high frequencies in the ClassicFM than in the ModFM, likely due to ModFM having a quick spectral decay (see Figure 1). In both cases, the sound envelopes are well approximated.

Figure 6 gives the distribution of the optimized synthesis parameters for the ModFM and ClassicFM implementation. Notice that the multiplier for the carrier frequencies, k, has the same distribution for ClassicFM and ModFM. In our architecture, k directly acts on the harmonic distribution of the spectrum. As we use the same set of target sounds for the evaluation of both systems, it seems natural to get the same k distribution, since ClassicFM and ModFM share the same spectral properties listed in Section 3.1. The values of k are concentrated around the value 2 and don't take on the rest of the possible values. One explanation can be that the target sounds are tones ranging from B to C and don't require high values of k. On the other hand, optimized modulation indices I are also low and very concentrated, around 50% higher for ClassicFM than for ModFM, which confirms Lazzarini's findings [11].

When we look at the carrier envelopes, we can discern two interesting cases. The first case is when these are all positives and look like the target tone envelop (see Trumpet 2 carriers or Piano 4 carriers [12]). Each carrier seems to contribute to the final tone in term of spectrum. The second case is when some envelopes are positives and look like the target tone envelop and some other are negative and look like the reverse of the target tone envelop (see Flute 4 carriers or Clarinet 4 carriers [12]). The negative envelops seem to counterbalance the effect of the positive ones to match the target spectrum.

Figure 5 shows the harmonics matching with 2, 4 and 6 carriers using ModFM for the trumpet and the viola. A
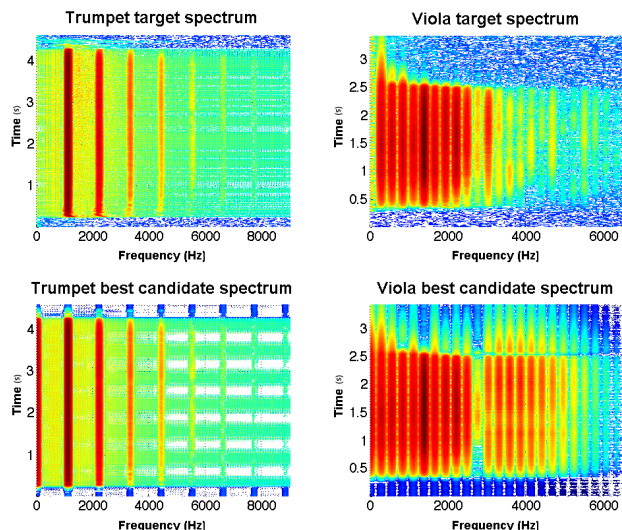
comparison between the target spectrogram and the best synthetic spectrogram for these two instruments with 4 carriers is given by the Figure 7. For both Viola and Trumpet, the first three harmonics are well approximated with 2 carriers. More carriers are required to match the following harmonics. With 4 carriers, the Trumpet parameter optimization seems to reach a plateau and adding 2 more carriers doesn't seem to improve subsequently the estimation. It is different for the Viola, going from 4 carriers to 6 carriers makes possible to finally match the 9th and 10th harmonics. If we look at the overall spectrograms of these two sounds, we can see that unwanted high frequencies are present in the synthetic sound. It might come from our limitation to only look at the 10 first harmonics but it might also be a limitation of ModFM synthesis. Indeed, Lazzarini pointed out that instrument designers willing to use ModFM should be concerned with avoiding aliasing when using high fundamental frequencies [11].

7. CONCLUSION AND FUTURE WORK

We have refined a system to optimize the parameters in a ModFM synthesis model to reproduce a given target instrument tone. This system is based on a pre-analysis of the target sound, matching through a genetic algorithm and reconstruction of the tone using ModFM synthesis. A study was conducted with various instruments and our results were compared. An application for parameter matching for a commercial synthesizer by Teenage Engineering [25] is actually under development.

We successfully use a genetic algorithm to help find the right parameters using ModFM as a synthesis technique to match a specific instrument tone. The comparative study also shows that GA gives generality and efficiency to parameter calibration as neither our fitness function nor other genetic parameters have to be modified when used with ModFM or ClassicFM. Finally, if we remove the harmonicity constraint on the target sound and on the ModFM syn-

thesis architecture, it seems possible to use GA and a different fitness function to explore the potential of ModFM synthesis to resynthesize inharmonic sounds.

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